4-1-2014

Home Foreclosures and Neighborhood Crime Dynamics

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Abstract We advance scholarship related to home foreclosures and neighborhood crime by employing Granger causality tests and multilevel growth modeling with annual data from Chicago neighborhoods over the 1998-2009 period. We find that completed foreclosures temporally lead property crime and not *vice versa*. More completed foreclosures during a year both increase the level of property crime and slow its decline subsequently. This relationship is strongest in higher-income, predominantly renter-occupied neighborhoods, contrary to the conventional wisdom. We did not find unambiguous, uni-directional causation in the case of violent crime and when filed foreclosures were analyzed.

Keywords foreclosures, crime, neighborhoods, Granger causality, multilevel growth models

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Background

The last half-decade has witnessed a record-number of home foreclosures in America, as risky mortgage underwriting practices and deteriorating employment prospects have wreaked havoc (Immergluck, 2011). Although many of these foreclosed homes have been resold, an estimated 644 thousand remain vacant nationwide at this writing. Even more sobering, an additional 711 thousand properties appear to be headed into foreclosure soon (Saulny, 2012).

The financial and psychological impacts of foreclosure upon individual owners and occupying households are not to be minimized. The impacts of concentrated foreclosures on neighborhoods have also proven devastating, however (Kingsley, Smith and Price 2009). As illustration, Immergluck and Smith (2006a) found in Chicago that every additional foreclosure within an eighth of a mile reduced a home's value by 0.9%; in low- and moderate-income neighborhoods the marginal impact was twice as large: 1.8%. Harding, Rosenblatt and Yao (2009) analyzed patterns in 13 states and 7 metro areas and estimated a 1.0% negative impact on housing sales prices resulting from each additional foreclosure within 300 feet, and roughly half that amount for foreclosures within 300-500 feet. If these estimates are even approximately correct, they imply that American neighborhoods have lost hundreds of billions of dollars in home equity purely from the negative externalities associated with home foreclosures over the last several years (Kingsley, Smith and Price 2009).

There are several likely mechanisms through which foreclosures get capitalized into lower proximate property values: visible under-maintenance of the vacant structure and grounds; health hazards associated with increased risks of fire and vermin infestations; unauthorized occupancy; and crime. We focus on the last factor in this paper. Foreclosures may spur crime nearby both directly and indirectly; for fuller discussions, see Immergluck and Smith (2006b); Taylor (2009); Katz, Wallace and Hedberg (2011); and Ellen, Lacoe and Sharygin (2013). Directly, vacant properties may provide attractive venues for criminals to hide and/or commit their illegal acts, as well as structures that are vulnerable to plunder (Raleigh and Galster, 2012). Loss of residents in the formerly inhabited dwellings means fewer "capable guardians" of the neighborhood (Taylor, 2009). Indirectly, visible disrepair and physical disorder around foreclosed properties can signal to potential lawbreakers an erosion of social control and collective efficacy in the neighborhood (Skogan 1990). Both directly and indirectly, foreclosures likely spur crime because of perceived-lower chances of apprehension on the part of potential criminals (Goodstein and Lee 2010; El**len, Lacoe and Sharygin 2013).**

What is less clear is whether temporal sequences and dominant causal processes differ between violent and property crimes and according to neighborhood context. Unfortunately, it is difficult to make definitive a priori predictions in these regards based on extant theory.

If the prime mechanism connecting foreclosures and property crime were that a dwelling is made vulnerable for burglary, one would predict that the relationship would wane soon after the vacancy occurs as valuables are quickly stripped from the property (Katz, Wallace and

Hedberg, 2011). On the other hand, if the prime mechanism were signaling disorder and weak collective efficacy, the impact on property crime could last a considerable period, conceivably until the dwelling is re-occupied. There may be less potential temporal variation in the response of violent crime, inasmuch as the main mechanisms may involve the venue and signaling effects of vacant properties.

By contrast, there is a conventionally accepted notion that foreclosures will have a more powerful crime-producing impact in weaker, more disadvantaged neighborhoods (Katz, Wallace and Hedberg, 2011). Because they have many disamenities it may take an extended period before foreclosed properties will be reoccupied (Immergluck and Smith, 2006b). Collective efficacy in such neighborhoods may be poised at a minimum threshold because they have relatively few homeowners to begin with. The loss of homeowners through foreclosure may be sufficient to tip the place into a crime upsurge. This upsurge may be unchecked if the disadvantaged area suffered from chronically lackluster police protection due to its lack of political clout (Taylor, 2009). This proposition has not been tested empirically, however, to our knowledge.

In an effort to probe these complex, often hard-to-predict patterns, we investigate the home foreclosures-neighborhood crime relationship in an innovative way that employs Granger causality and multilevel growth model techniques. Specifically, we analyze in a dynamic framework annual single-family home foreclosure and crime data in Chicago neighborhoods over the 1998-2009 period. We find that completed foreclosures temporally lead property crime and not vice versa, though such is not the case for violent crime. More completed foreclosures during a prior year both substantially increase the level of neighborhood property crime and slow its decline subsequently. Neighborhood characteristics moderate this relationship, however, in a manner contrary to the conventional wisdom.

Foreclosures, Crime and Neighborhood Dynamics: Past Research and a New Approach

Drawing causal conclusions from empirical analyses of the home foreclosure / crime relationship is complicated for two fundamental reasons: endogeneity and unobserved heterogeneity. First, there are equally plausible reasons that causation runs in the opposite way than is popularly conceived. Absentee landlords in neighborhoods with rising crime rates (perhaps having nothing to do with foreclosures) will likely be faced with falling property values and skyrocketing vacancies as demand for their neighborhoods withers (Hipp, Tita and Greenbaum, 2009; Hipp 2010). They may respond by reducing upkeep, withholding property tax payments and, in extreme cases, defaulting on their mortgages. Analogously, owner-occupants in such rising-crime neighborhoods may find themselves "under water" if their property values fall below outstanding mortgage balances. They, too, may choose to exercise their option of default. Thus, positive associations between trends in neighborhood crime and foreclosure rates may be indicative of the former causing the latter, not vice versa.

The second complication is that the observed foreclosure / crime relationship may be spurious due to heterogeneous, unobservable neighborhood characteristics. It is likely that several characteristics of a neighborhood—the location of properties vis-a-vis the street, access to mass transit, the presence and design of public spaces and facilities—will independently affect both how many foreclosures and how much crime will be observed there. These idiosyncratic features may shape the attractiveness and prospective quality of residential life of the neighborhood from the perspective of household demanders, and for entirely different reasons influence crime rates, such as through the built environment's impact on routine activity patterns and "defensible spaces." To the extent that these neighborhood features are heterogeneously distributed and unobserved (i.e., uncontrolled statistically) they can create omitted variable bias producing in the extreme an apparent correlation between foreclosure concentrations and crime rates that is wholly spurious.

In the pages of this journal, Immergluck and Smith (2006b) were the first to tackle these challenges with a multivariate quantitative analysis. They explored the cross-sectional relationship between the annual rate of foreclosed single-family properties in a census tract in Chicago and crime rates there during 2001, controlling for a host of 2000 demographic and socioeconomic characteristics of the population that might be expected to be related to crime. They found that tracts with a one percentage point-higher 2001 rate of foreclosures had a 2% higher 2001 violent crime rate, all else equal, though the relationships for property crime and total crime rates were not statistically significant. They employed a Hausman test to ascertain if endogeneity bias was present and concluded it was not.[1] Potential selection bias was not considered. The path-breaking efforts of Immergluck and Smith (2006b) led to a host of recent, increasingly sophisticated econometric studies of this phenomenon.

Goodstein and Lee (2010) analyzed a U.S.-wide panel of annual county data from 2002-2007, employing instrumental variables to deal with potential endogeneity bias and fixed-effects to deal with unobserved heterogeneity. They found that counties with a one percentage point-higher annual rate of foreclosures would be expected to have a 10% higher annual burglary rate in the following year, all else equal. In addition, foreclosures evinced some positive associations with larceny and assault rates, though the relationships were sensitive to the precise panel employed. Robbery, auto theft, rape and murder were not associated with foreclosures. Unfortunately, the large geographic scale at which the relationships were measured in this study is problematic, since the causal processes operating behind the foreclosure - crime relationship are likely varying at a finer-grained spatial level within a county.

Cui (2010) attempted to overcome this shortcoming with quarterly, block face data from Pittsburgh. Cui employed geo-coding of point-data to match proximate foreclosures and crimes for the 2006-2009 period. For each foreclosure she identified crimes within a 250-foot radius and those within an equal-area concentric ring from 251-353 feet (and not within 250 feet of another foreclosure), arguing that these constituted treatment and control groups. To overcome both endogeneity and unobserved heterogeneity, Cui executed a difference-in-differences regression model wherein pre- and post-foreclosure differences in crimes across treatment and control areas were compared. Cui concluded that quarterly violent crime rates were 15% higher within 250 feet of a foreclosed and vacant property than in comparable areas less proximate. It was only when a foreclosed property became vacant, however, that the negative impact transpired. The magnitude of this relationship with property crimes was similar but not as statistically significant. Unfortunately, Cui deemed areas with high concentrations of foreclosures unsuitable for either treatment and control areas, so they were omitted from the analysis.

[1] However, when Cui (2010) replicates a cross-sectional model like Immergluck and Smith's she finds a variety of implausible relationships. Moreover, she finds that crime rate strongly predicts foreclosures three years later, suggesting that endogeneity is indeed worrisome.

Moreover, the implicit assumption that proximity variations within 250 feet make no difference and are unrelated to block face conditions is questionable.

Ellen, Lacoe and Sharygin (2013) also employed point-level, quarterly crime and foreclosure data to examine relationships in New York City during 2004-2008. Like Cui (2010), they utilized a difference-in-differences estimation strategy comparing block face crime levels before and after foreclosures occurred to analogous changes in others in the same police precinct without foreclosures. They included both block face fixed effects and police precinct-quarter fixed effects to surmount issues of unobserved heterogeneity. They further tested for endogeneity by ascertaining if future foreclosures over the next six quarters predicted crime in the current quarter, which it did not. Ellen, Lacoe and Sharygin found that in their preferred specification that a marginal increase in foreclosures resulted in 3% more total crimes, almost 6% more violent crimes, and 3% more public nuisance crimes (but not more property crimes) on the block face in the subsequent quarter. This relationship seemed to appertain primarily after a threshold of two foreclosures on the block face was surpassed, however. Moreover, it appeared that crime was not merely relocated from other parts of the precinct to block faces with more foreclosures, and instead represented a net increase. Like Cui (2010), they found that it was the period after which a foreclosed home became vacant when crime impacts were manifested.

Katz, Wallace and Hedberg (2011) explored the finely grained timing of foreclosure-crime relationships using monthly 2003-2008 data aggregated to census blocks in Glendale, AZ. They estimated a random-effects model of the monthly crime rate in the block as a function of the contemporaneous and three prior monthly lagged values of foreclosure rates, demographic and land use control variables, and a quadratic in time. Their model revealed that for every additional foreclosure there was a cumulative impact of 12 more property crimes and 3 more violent crimes (per thousand population), though their random effects showed considerable variation in this impact across blocks (especially for property and total crime rates). They concluded that foreclosures caused an immediate flux followed by a brief increase in crime—no more than four months for drug crimes and three months for other categories. However, it is unclear the degree to which these estimates are influenced by endogeneity bias, though the lag specification offers some confidence in this regard.

In sum, the recent spate of sophisticated econometric analyses have come to a remarkable degree of consensus that home foreclosures during the first decade of the twenty-first century in U.S. urban neighborhoods indeed lead to more crime (of one sort or another) nearby. This conclusion appears robust to the scale of neighborhood or time period over which data are observed, and holds when a variety of techniques are employed to minimize the potentially biasing influences of endogeneity and unobserved heterogeneity.

The research we report in this paper offers an explicit temporal, dynamic focus on the topic, thereby advancing from this foundational work above in several ways. First, we explore the issue of endogeneity by employing adapted Granger causality tests to ascertain if crime does, indeed, temporally lag foreclosures and not *vice versa*.[2] Second, after establishing a plausible causal sequence from the prior step, we estimate with a multilevel growth model how foreclosures affect the trajectory (as well as level) of neighborhood crime, employing random effects to deal with unobserved heterogeneity. Third, we investigate the degree to which the prior relationships are sensitive to neighborhood groups distinguished by housing market strength.

Our paper is organized as follows. We begin describing the sources and nature of our longitudinal data for the city of Chicago, how we standardized and adjusted indicators, and our cluster analysis employed to ascertain neighborhood groups in Chicago. Second, we provide a portrait of trends in foreclosures and crime in Chicago during our analysis period, both overall and by group. Third, we present our adapted Granger causality tests that ultimately demonstrate that completed foreclosures lead property crime temporally. Fourth, we describe our multilevel growth model and present its estimated parameters indicating that more foreclosures lead both to an elevated initial level of property crime and its slower reduction over time. We also demonstrate how the foregoing multilevel growth model results are sensitive to neighborhood context. We offer conclusions, caveats and implications in the final section.

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[2] Cui (2010) and Ellen, Lacoe and Sharygin (2011) explore the causality issue in a conceptually similar way by testing if the temporal leading value of foreclosures predicts crime.

Data and Measures

Geographic Unit of Analysis

In 2003, the MacArthur Foundation of Chicago funded an ambitious initiative to improve conditions in distressed urban neighborhoods: the New Community Program (NCP). A 10-year, $47 million effort, NCP is a comprehensive effort to engage community-based groups to attack multiple problems simultaneously — in education, workforce development, housing, social services, and public policy. Managed by the Local Initiatives Support Corporation of Chicago (LISC/Chicago), NCP focuses its efforts on 14 neighborhood areas in Chicago with varying challenges. Inasmuch as the research reported here was completed as part of a larger evaluation of NCP, we collected data corresponding to the geographies of the 14 NCP neighborhoods, plus the remaining 66 Community Areas specified by the City of Chicago.[3] We emphasize that although these geographic units are relatively large (typically several census tracts), they have longstanding social meaning in Chicago.

In this study we use data provided by the Metro Chicago Information Center. MCIC obtained data from a variety of secondary sources, transformed them to create counts and sums for the Census tracts within Chicago, aggregated them to create measures at we hereafter call the "neighborhood" level, and then standardized them to adjust for different neighborhood population sizes.[4]

Neighborhood Groups

We wish to examine potential variations in foreclosure-crime dynamics across different neighborhood contexts. To accomplish this categorization

[3] A map showing these 80 neighborhoods is available from the authors. Note that some of the traditional 77 Community Areas of Chicago were split for our analysis because parts were outside NCP boundaries. With these few exceptions, our 80 neighborhoods follow the encompassing boundaries of their constituent census tracts.

[4] The Census tract designations used for these transformations are the definitions created after the 2000 Decennial Census; data collected or assembled using earlier designations was transformed to the 2000-era designations using the relational matrices published by the US Census Bureau. For most of the neighborhoods, the definitional boundaries align with tract boundaries such that the neighborhood-level measure is the aggregation of the tract-level measure. In cases where this is not true, the tract values were apportioned between multiple neighborhoods based on the distribution of the tract's population between the multiple neighborhoods.

of contexts in a meaningful, multi-dimensional way we undertook a cluster analysis of the 80 aforementioned Chicago neighborhoods, based on a large number of indicators conceptually related to the "market strength" of the area; see Appendix Table A1. These indicators measured both 2000 levels of and pre-2000 changes in indicators of: median income, racial ethnic composition, mortgage market activity and housing stock characteristics. We applied several clustering algorithms and found that they all led us to specify a five-fold typology[5]

Chicago Neighborhood Groups

Group I Moderate income, predominately black residents; housing is mostly owner-occupied, single-family units

Group II Moderate income, predominately white residents – about one quarter of whom are foreign-born; with a mix of single-family and multi-unit owner-occupied dwellings

Group III Moderate income, predominantly Hispanic residents – almost 40% are foreign-born; housing is mostly smaller multi-unit dwellings, split between owner-occupiers and renters

Group IV Low income; variety of racial and ethnic predominance;

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[5] Cluster analysis was used to create the neighborhood grouping used in this paper. This technique is widely used to sort cases (people, things, events, neighborhoods, and so on) into groups, or clusters, so that the degree of association is stronger among members of the same cluster and weaker among members of different clusters. The procedure was applied to classify all Chicago neighborhoods, and more than 20 variables were used to group these neighborhoods, including measures of economic context, housing market dynamics, and racial/ethnic diversity of neighborhoods; see Appendix Table A1. These measures were assembled for the period 2000-2005, in order to capture the "starting context" for the NCP initiative. In general, a good cluster solution is one in which each cluster is very different from other clusters ("between-cluster heterogeneity") and in which units in each cluster are as similar as possible ("within-cluster homogeneity"). We used the Ward clustering method. The statistical diagnostics available for cluster analysis were calculated and examined, and they confirm that the resulting five clusters of neighborhoods largely differ from one another. In addition, tests were conducted to assess the "goodness of fit" of neighborhoods with their groups (including an examination of the extent to which neighborhoods differ from their cluster, on average, as well as sensitivity tests comparing findings before and after the exclusion of a potentially "outlier" neighborhood). These tests provide further confidence in the five clusters.

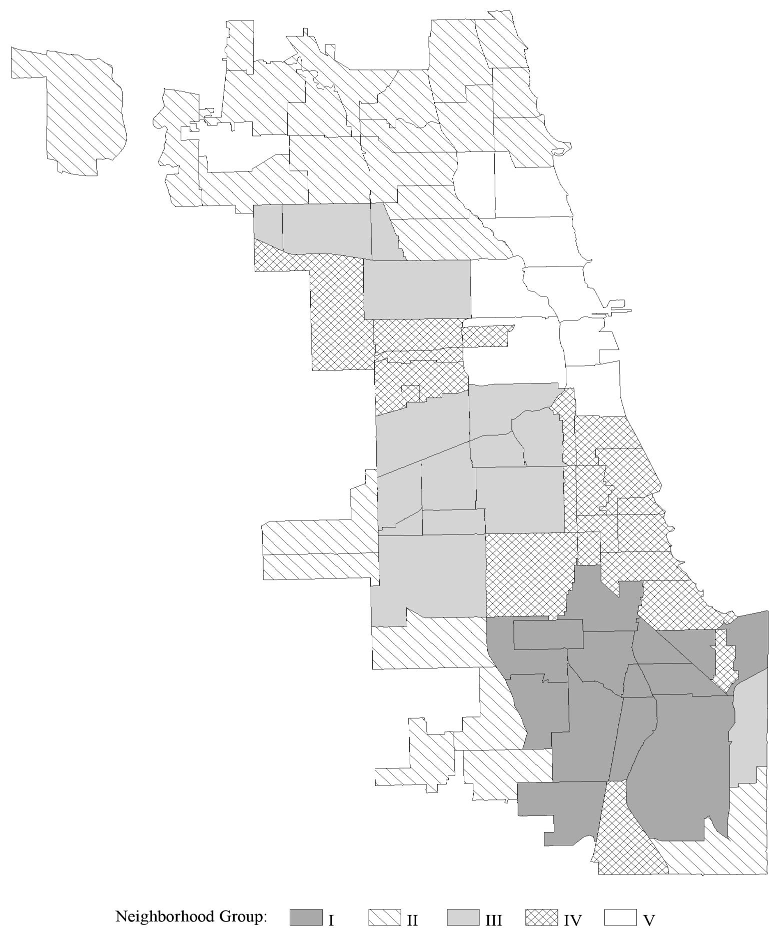
housing is mostly renter-occupied, large multi-unit dwellings

Group V High income; variety of racial and ethnic predominance; housing is mostly large multi-unit dwellings, with more renters than owners

The neighborhood groups are primarily distinguished by the income and race/ethnicity of the neighborhood residents; descriptive statistics for the five neighborhood groups are presented in Appendix Table 1. For example, Chicago neighborhoods where the average (mean) household income is around the city average (i.e., middle and working class neighborhoods) are split by race/ethnicity between three groups. Neighborhoods with predominantly black residents are in Group I, those with predominantly white residents are in Group II, and neighborhoods where a large proportion of the residents are Hispanic are in Group III. The other two groups contain the neighborhoods where the average incomes are below (Group IV) and above (Group V) the city average. The neighborhoods in Groups IV and V have a wider variety of racial and ethnic compositions compared to the first three groups.

The neighborhoods in the five groups also differ in terms of their housing configuration. Two of the moderate income groups — neighborhoods with predominantly black residents (Group I) and those with predominantly white residents (Group II) — consist of mostly owner-occupied housing. Most of the residences in the Group I neighborhoods are single-family dwelling units, while those in Group II are a mix of single-family and large, (five or more) multi-unit buildings. The other moderate income group, neighborhoods with a considerable proportion of Hispanic residents (Group III), is split between rental and owner-occupied housing, the majority of which are small, (two to four) multi-unit buildings. Finally, the low income (Group IV) and high income (Group V) neighborhood groups have similar housing configurations — large, multi-unit buildings where the majority of residents are renters.

Each group of neighborhoods is somewhat spatially contiguous; see Map 1. The high income neighborhoods (Group V) are clustered around the central business district of the city (known as the Loop) — this neighborhood group includes all of Central Chicago as well as North Side and West Side neighborhoods that border Chicago's downtown. The low income neighborhoods (Group IV) are mostly in Chicago's South Side, although a few are in the West Side. The spatial distribution of the moderate income neighborhood groups reflects the historical racial distribution of Chicago, with the neighborhoods having a predominately white population (Group II) in the North Side, those with predominately black populations (Group I) in the South Side, and those with a relatively high concentration of Hispanics (Group III) in the West Side.



Map 1. Chicago Neighborhood Groups Produced by Cluster Analysis

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The five neighborhood group classification is used to represent neighborhood context in the analyses presented here. These groups reflect multidimensional differences in important neighborhood characteristics that we believe distinguish contexts according to strength of local housing market and other aspects that are likely to influence the magnitude of the foreclosure-crime relationship.

Foreclosure Data

Counts of filed and completed foreclosures on single-family homes for the years 1998 to 2009 originated from administrative records kept by the Cook County Circuit Clerk's Office. Foreclosure filings count properties where a complaint has been filed against the homeowner requesting that foreclosure proceedings be initiated. Foreclosure completions count of the number of forecloses whose resolution was an auction of the property in question (foreclosure filings that are resolved in other ways are not classified as completed).[6] Both counts were aggregated to the neighborhood level, summed for the calendar year, and standardized by the number of single-family, owner-occupied dwellings, in 10,000s.

Unfortunately, neither filed or completed foreclosure indicators give a precise estimate of when a foreclosed property becomes vacant and then (possibly) is occupied again. But, because these indicators likely bracket the desired figure, we conducted our analyses in parallel using both.

Crime Data

Data originate from crimes reported by the Chicago Police Department for the period 1991 to 2009, classified using the Uniform Crime Report (UCR) typology. Each record reflects a police report of an incident, which may include multiple crimes.[7] MCIC geo-coded these reports, aggregated them to the neighborhood level, summed them for the calendar year, then standardized them across neighborhoods by dividing by 2000 population in 10,000s. Crimes were divided into two types: property (arson, auto theft, burglary, and larceny-theft) and violent (assault, murder, rape, and robbery). Geographic variations in these crime rates across Chicago neighborhoods are portrayed in Maps 2 and 3.

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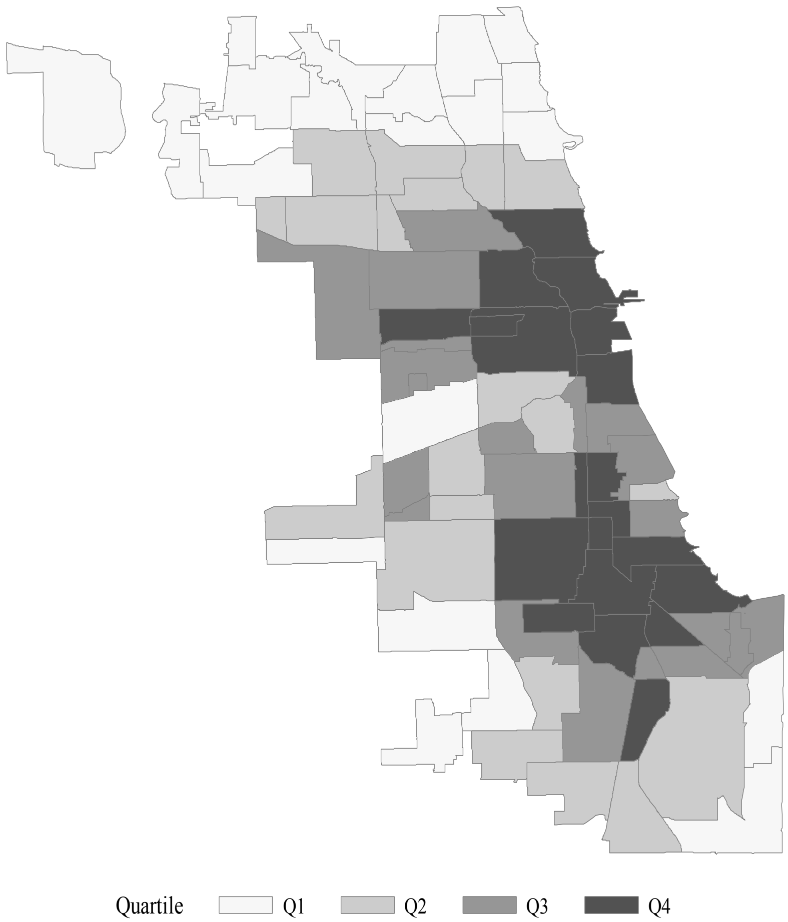
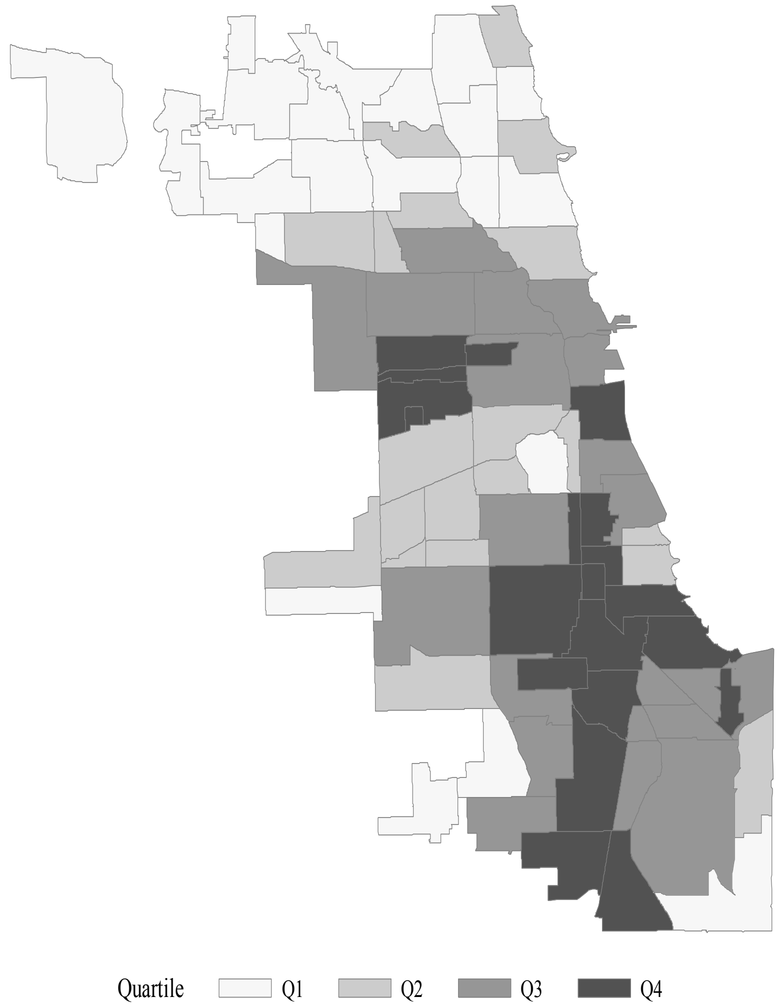
[6] Both filed and completions data exclude ownership transfers that occur as the result of financial distress (short sales or deed-in-lieu-of-foreclosure transactions).

[7] With multiple incidents the report is classified in the UCR category of the most serious crime (generally, the crime with the highest potential penalty). Note that these are police reports and do not reflect later adjudication of the incident (e.g., an assault recorded on the initial report as a criminal act later adjudicated as justifiable self-defense is still included).



Map 2. Chicago Property Crime Rates, 2003 [***Note:*** Property crime rate is number of reported crimes per 10,000 population.]



Map 3. Chicago Violent Crime Rates, 2003

We recognize that these data have shortcomings. As they originate from police reports, unreported crimes are not included and the underreporting rate may not be constant across neighborhoods, depending on the crime (Baumer, 2002; Goudriaan, Wittebrood and Nieubeerta, 2006). We could only obtain annual crime counts aggregated to the neighborhood.

Other Data

Population, income and housing unit data were extracted from the 2000 Census summary file 3 tabulations. Data regarding home purchase loans for owner-occupied homes in one- to four-unit dwellings (number of loans issued, aggregate amount of lending, and median loan amount; the former two standardized by single-family, owner-occupied dwellings) was tabulated from annual Home Mortgage Disclosure Act documents 1998-2009. Commercial land area was obtained from an aerial survey commissioned by the Chicago Metropolitan Agency on Planning in 2000.

LOESS Curves

One issue pertinent to the visual display of trends for indicators such as the ones used here is the level of volatility in the data. As our unit of analysis represents a fairly high level of aggregation compared to the original scale of measurement, the effect of random fluctuations and other noise-inducing events can be magnified. This may lead to inappropriate emphasis on points with high levels of variation and increased difficulty in identifying the overall course of the trend. Thus, we used smoothing techniques to prepare the trend charts shown below. Specifically, the trend charts show the actual indicator values (represented by small circles) superimposed upon a curve which represents the results of a local, non-parametric regression technique (LOESS). At each point of the trend, a low-degree polynomial is fit to a subset of the entire set of data consisting of those points nearest to the point in question (i.e., its neighbors). The polynomial is fit using a weighted regression procedure, giving higher weight to points that are close neighbors and lower weights to those that are further away.[8]

Recent Trends in Foreclosures and Crime in Chicago

As can be seen in Figure 1 and Table 1, both property and violent crime rates have declined in Chicago since the early 1990s, following the

[8] While the LOESS function is parametric within a single "neighborhood" of the data, the overall function — the compilation of the local regression results for each point — fit to the trend is non-parametric. Weighted moving averages are a simple example of a LOESS function, where the local polynomial regression function has a degree of 0. For the LOESS functions estimated for the indicators, a higher degree polynomial was used so that shifts in trend direction would be more readily identified.

national trend. The decline was not uniform across the city's neighborhoods, however, with generally greater declines in crime for neighborhoods with initially higher levels of crime. Specifically, the crime rates for the neighborhoods with the highest amount of crime declined at a higher rate, relative to other neighborhoods. An exception to this is the moderate income neighborhoods with a predominately black population (Group I), who on average had crime rates above the city rates. While the difference between the city rates and the neighborhood rates was not as great for the Group I neighborhoods compared with the other higher-crime areas, the rate of decline in the crime rates for the neighborhoods in this group was much slower compared with the other neighborhoods and the city as a whole.

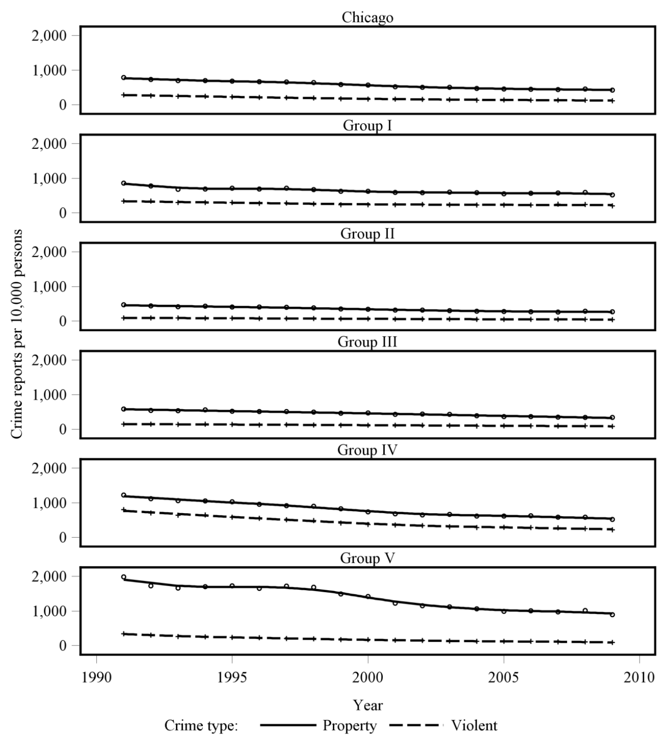


Figure 1. Property and Violent Crime Reports per 10,000 Persons, Chicago Total and by Neighborhood Group, 1991-2009. [***Source:*** Authors' analysis of data assembled by Metro Chicago Information Center. ***Notes:*** Table values are the annual rate and percentage change averaged across neighborhoods as indicated in the column labels. Standard deviations are shown in parenthesis.]

Table 1. Crime and Foreclosures in Chicago: Neighborhood Annual Average Rate and Percentage Change, by Group, 1998-2009

Characteristic	All	I	II	III	IV	V
Violent Crime per 10,000 population						
Annual Rate	168.90	235.30	55.30	104.60	323.70	135.70
	-137.00	-61.20	-33.60	-49.30	-147.20	-83.60
Annual Percentage change	-3.96	-2.33	-3.49	-2.35	-5.98	-6.01
	-2.77	-0.69	-2.76	-2.61	-2.42	-1.94
Property Crime per 10,000 population						
Annual Rate	546.30	590.20	302.50	406.60	666.90	1166.90
	-413.20	-127.70	-93.70	-105.50	-242.00	-978.80
Annual Percentage change	-3.35	-2.05	-3.24	-3.09	-4.21	-4.10
	-1.45	-0.67	-1.43	-0.88	-1.66	-1.02
Filed Foreclosures per 10,000 single family housing units						
Annual Rate	364.40	390.80	122.90	269.40	798.50	138.90
	-392.90	-108.60	-61.60	-199.10	-544.70	-87.30
Annual Percentage change	4.26	3.31	10.65	12.90	-3.86	-9.31
	-11.73	-2.15	-10.67	-10.08	-6.57	-12.27
Completed Foreclosures per 10,000 single family housing units						
Annual Rate	229.20	247.30	56.50	139.30	561.90	54.30
	-296.90	-84.90	-40.90	-154.00	-410.10	-36.60
Annual Percentage change	-2.32	-2.70	2.51	4.52	-8.34	-13.97
	-10.73	-1.34	-11.52	-9.33	-5.97	-12.26

Source: Authors' analysis of data assembled by Metro Chicago Information Center. ***Notes:*** Table values are the annual rate and percentage change averaged across neighborhoods as indicated in the column labels. Standard deviations are shown in parenthesis.

As can be seen in Figure 2 and Table 1, Chicago's rate for both filed and completed foreclosures has radically changed direction over time, with the last peak occurring during the previous recession in the early 2000s. After falling for several years, the filed foreclosure rate began rising again in 2006; the completed foreclosure rate also began increasing shortly thereafter but has yet to catch-up to the filed foreclosure rate. The low income neighborhoods (Group IV) have been the hardest hit by foreclosures, both currently and during past upsurges; see Map 4. While the level of foreclosures is not as high, the moderate income neighborhoods with predominately black residents (Group I) have also historically been disproportionately affected by foreclosures; in fact, for these neighborhoods, the rate of filed foreclosures did not appreciably decline after the early 2000s recession. The neighborhoods in these two groups, along with the moderate income neighborhoods with concentrations of Hispanic residents (Group III), have the largest divergence between their filed and completed foreclosures in recent years; this suggests that many of these foreclosures are related to sub-prime mortgages. Neighborhoods in the other groups (II and V) generally have lower rates of foreclosures, particularly having only very small trend responses to the previous recession. While the filed and completed foreclosure rates in the high income neighborhoods (Group V) have remained close in both size and trend, the filed foreclosure rate has begun to outpace the completed foreclosure rate in the moderate income neighborhoods with predominately white residents (Group II), possibly in response to the duration of the post-housing market collapse recession.

In sum, the portraits of both crime and foreclosure trajectories in Chicago evince substantial variation across neighborhood types. This suggests that both neighborhood context (as captured by the neighborhood groups) and unique characteristics of neighborhoods influence an indicator's trajectory. Moreover, it suggests that contextual factors should be considered when assessing the foreclosure-crime relationship, which we do in the last section of this paper. [Further details of the annual crime and foreclosure data are provided in Appendix Table 2.]

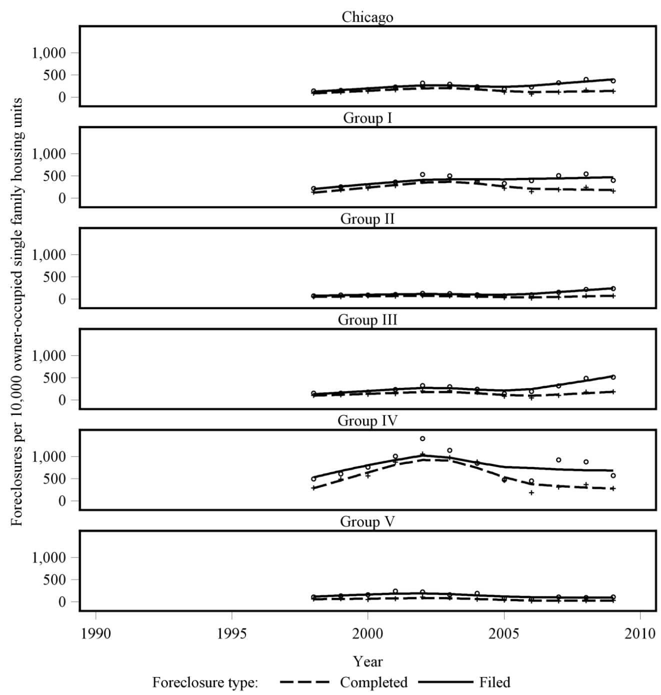
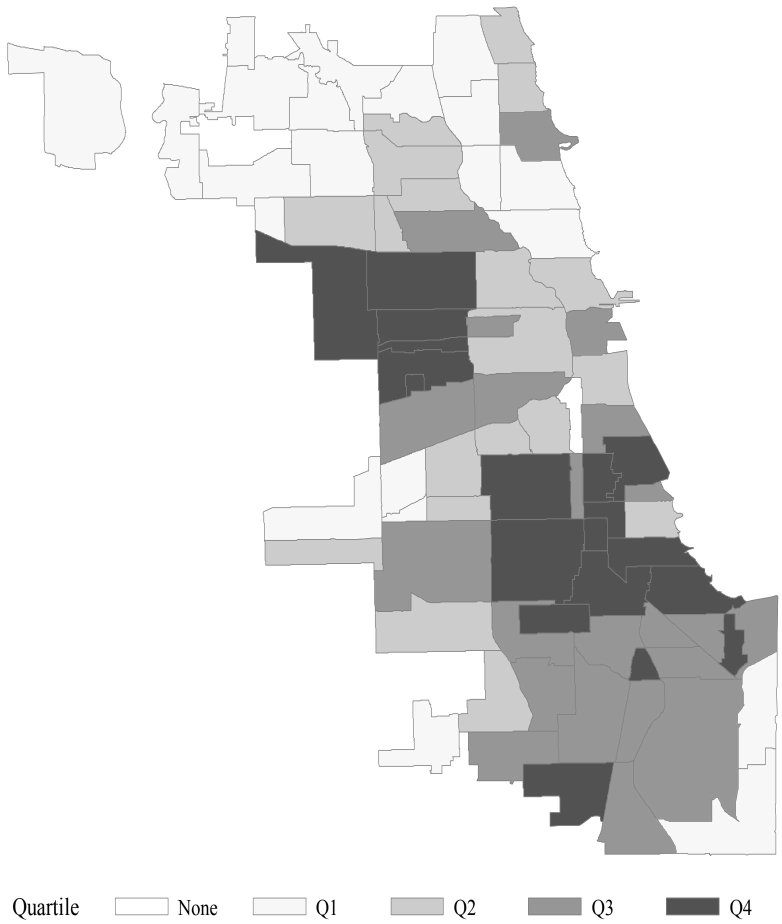


Figure 2. Filed and Completed Foreclosures per 10,000 Owner-Occupied Single Family Housing Units, Chicago Total and by Neighborhood Group, 1998-2009. [***Source:*** Authors' analysis of data assembled by Metro Chicago Information Center. ***Notes***: The plotted line for each indicator is smoothed using a nonparametric locally weighted regression technique known as LOESS. See text for further information.]



Map 1. Chicago Completed Foreclosure Rates, 2003. [***Note:*** Completed foreclosures rate is the number of completed foreclosures of single-family properties per 10,000 single-family owner occupied homes.]

Do Foreclosures Lead or Lag Crime? Granger Causality Tests

Analysis Method

Now that we have examined the trends in crime and foreclosures in a descriptive fashion for Chicago and its five neighborhood groups, we address the analytical question of whether at the individual neighborhood level there is any distinct temporal sequence in these indicators. We do so by employing a variant of Granger causality test. Granger Causality describes a particular statistical relationship that can exist between two time series.[9] Formally, a time series X may be said to "cause" another time series Y if and only if the expectation of Y given the history of X is different from the unconditional expectation of Y:

$$E(Y|Y_{t-k}, X_{t-k}) \neq E(Y|Y_{t-k})$$

where t indexes time and t-k indexes some number of lags (previous values) of Y (i.e., $Y_{t\text{-}1}$, $Y_{t\text{-}2}$, etc.) Since X can only change the expected value of Y if there is a statistical relationship between the two time series, the test of a Granger Causal relationship can be structured as a test of whether the fit of the model of Y improves when X is added as a predictor.

We test for Granger Causality by assessing the joint significance tests of the estimated coefficients for the candidate predictor. First, an autodependence model of the outcome is estimated:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \ ... + \beta_k Y_{t-k} + \varepsilon_t$$

where k is the number of lags used to account for the dependence of values of the outcome in one period on its value in past periods.[10] A second model, including the candidate predictor, is then estimated:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \ ... + \beta_k Y_{t-k} + \gamma_1 X_{t-1} + \gamma_k X_{t-k} + \varepsilon_t$$

If the γ parameters are jointly significant, this provides evidence of the existence of a Granger Causal relationship between X and Y.[11] We use k=2 for our analyses, given the relatively short panel of annual observations

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[9] The use of the causal in the name of the test and throughout this section is a reference to the particular statistical relationship, not to be mistaken for conceptual causality and/or causal mechanisms.

[10] The value of k is not determined empirically as Granger Causality is a "brute force" method. Generally, the value of k is set high enough to ensure that the autodependence of the outcome is accounted for within the limits of the input data

[11] Note that the Granger Causality test relies on overfitting to ensure that all autodependence is removed from the data. This overfitting is harmless in regards to bias, meaning that it does not imperil the validity of the statistical significance tests. However, overfitting causes estimator inefficiency and so results in uninformative coefficient estimates. In other words, Granger Causality tests whether there is a relationship (i.e., its existence) but is uninformative in regards to the strength or direction of effects of X on Y.

from 1998-2009.[12]

A further adaptation of the Granger Causality test is necessary when the input data concern multiple geographic units, as is the case here. Recall that the models specified above include a single error term, ε_t, which accounts for random disturbance associated with individual time periods. Since the data used here include multiple units, random disturbances associated with the individual units must also be accounted for in the model specification. Thus, the models specified to conduct the Granger Causality tests reported on here include two-way random effects (i.e., ε_t and ε_i, where i indexes neighborhoods) to account for the structure in the error term.

Our focus here is on identification of time-shifted (asynchronous) associations or lead/lag relationships between foreclosure and crime rates. Thus, we assess Granger Causality using each indicator as the outcome. That is, using the notation from above, we tests whether X causes Y and whether Y causes X. There are four possible outcomes, as follows (where an arrow signifies Granger causality):

1. $X \rightarrow Y; Y \nrightarrow X$
2. $X \nrightarrow Y; Y \rightarrow X$
3. $X \rightarrow Y; Y \rightarrow X$ (or$X \leftrightarrow Y$)
4. $X \nrightarrow Y; Y \nrightarrow X$

Interpretation is straightforward for three of these cases. For outcomes 1 and 2, X leads Y or vice versa, while for outcome 4, the null hypothesis of no time-shifted relationship cannot be rejected. Interpretation of the third outcome is less determinable: X and Y each cause the other, which may be due to a feedback loop, the influence of a third, unaccounted for variable, or something else.

Thus, this modeling strategy allows identification of time-shifted relationships between multiple variables, including identification of situations where lead-lag relationships between two indicators are complimentary (outcome 4). In addition, the model specification accounts for the correlated nature of the error term which arises from the structure of the data (i.e., time series for multiple geographic units).

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[12] Results are robust to k=1 as well, though we did not have adequate observations to estimate a model with k=3

Results

The chi-squared statistics for joint significance of the one-year and two-year lagged predictors are presented in Table 2. Not surprisingly given our use of annual rates, both violent and property crime rates are synchronous (i.e., mutually causal as in case 3 above), as are filed and completed foreclosure rates. More to the point, there are some foreclosure - crime relationships for which we cannot reject the null hypothesis of no time-shifted relationship (case 4 above): filed foreclosures and property crime; completed foreclosures and violent crime. Moreover, filed foreclosures and violent crime are synchronous (i.e., mutually causal as in case 3 above). However, completed foreclosures lead property crime but there is no relationship in the opposite direction (case 1 or 2 above). It is only in this instance that we have unambiguous support for uni-directional causation. We therefore have confidence that estimates produced by our multilevel growth model of completed foreclosures and property crime below will not be seriously biased by endogeneity; we do not have similar confidence in the relationship with violent crime and so do not estimate a multilevel growth model of it.

Table 2. Time-Shifted (Lead-Lag) Relationships between Foreclosure and Crime Rates, Chicago Granger Causality Test Statistics

	Property Crime as outcome	Violent Crime as outcome	Completed Foreclosures as outcome	Filed Foreclosures as outcome
Property crime as predictor	—	**13.30**	0.06	3.69
Violent crime as predictor	**19.30**	—	3.16	**18.90**
Completed foreclosures as predictor	**4.95**	3.78	—	**25.80**
Filed foreclosures as predictor	2.85	**41.40**	**213.00**	—

Source: Authors' analysis of data assembled by Metro Chicago Information Center. ***Notes:*** The table is not symmetric: rows indicate predictors and columns indicate outcomes. See text for further information regarding methods. The test statistics use the chi-square distribution with two degrees of freedom; tests that are statistically significant at $p<.10$ ($\chi^2>4.605$) are indicated in bold

These results may seem curious in light of prior literature examining the relationship between crime and foreclosures, where the typical result is a stronger relationship between foreclosures and violent crime than for foreclosures and property crime. However, these results are not necessarily contradictory to ours, as our Granger analysis is testing the nature of the relationship between the indicators rather than its strength. In fact, the mutually-causal nature of the foreclosure-crime relationship found here may be an explanation of for the "typical" result – that is, the relationship between foreclosures and violent crime is characterized by a feedback effect which could appear as a stronger relationship in the uni-directional tests typically employed.

How Do Foreclosures Affect Property Crime? Multilevel Growth Model Tests

Analysis Method

We specify a multilevel growth model to address this question. This model decomposes the longitudinal trend by specifying it as a function of time with two parameters: a starting level and a rate of change. In addition, this method allows for both estimation of overall effects and assessment of variation among the neighborhoods. Multilevel models, also known as hierarchical linear models (HLM), are generally referred to as growth models when applied to longitudinal data. The basic characteristic of these models is the inclusion of random neighborhood effects, to account for the influence of neighborhoods on their repeated observations.[13] These random neighborhood effects indicate the degree of variability in the change model main effects that exists within the population of neighborhoods, allowing estimation of the distribution of the main effects among neighborhoods. They also help remove potential bias due to geographic heterogeneity in unobservables.

Suppose the outcome of interest (y) is hypothesized to have a linear, additive change process, which could be represented as:

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[13] The multilevel model random effects are different from the random effects commonly used in econometric time series models (sometimes referred to as fixed effects models). In the multilevel formulation, the random effects are equivalent to main effects, with the descriptor "random" referring to the nature of the neighborhoods (i.e., they are theoretically drawn at random from some larger population). In contrast, the econometric random effects describes the effect of individual differences (i.e., random disturbance), which is necessary to account for to generate unbiased estimates for the main effects. For an introduction to multilevel models, see Kreft and de Leeuw (1998).

$$y_{it} = \alpha_i + \beta_i x_{it} + \varepsilon_{it}$$

where y_{it} is the level for neighborhood i at time t, x_{it} is the measure of time for neighborhood i at time t, α_i and β_i are the intercept and slope parameters for neighborhood i (i.e., the starting level and amount of change per unit change in x_{it}), and ε_{it} is the residual (error) for neighborhood i. The intercept and slope are random variables (i.e., the random effects), with their variation across neighborhoods modeled as:

$$\alpha_i = \alpha + \mu_{\alpha i}$$

and

$$\beta_i = \beta + \mu_{\beta i}$$

where α and β represent the fixed effects for the intercept and slope (somewhat analogous to the mean of the random effects) and $\mu_{\alpha i}$ and $\mu_{\beta i}$ represent the random variation of neighborhoods. Substituting the fixed effects equations into the first yields the combined model:

$$y_{it} = \alpha + \beta x_{it} + \mu_{\alpha i} + \mu_{\beta i} x_{it} + \varepsilon_{it}$$

To fit this model, two fixed effects (α and β) and four variance/covariance parameters are estimated: the residual variance (var(ε_{it})), the slope and intercept variance (var($\mu_{\alpha i}$) and var($\mu_{\beta i}$)), and the covariance between the slope and intercept (cov($\mu_{\alpha i}$, $\mu_{\beta i}$)). The variance/covariance parameters indicate the distribution of the main effects among the neighborhoods.

$$y_{itk*} = \sum_k \delta_k(\alpha_{ik} + \beta_{ik}x_{itk} + \varepsilon_{itk})\, y_{itk*} = \sum_k \alpha_k\delta_k + \beta_k\delta_k x_{it} + \delta_k\mu_{\alpha i} + \delta_k\mu_{\beta i}x_{it} + \delta_k\varepsilon_{it}$$

Our dependent variable is the annual count of property crimes in each neighborhood, regressed on the count of completed foreclosures in the previous year, consistent with our Granger causality findings. Here we use counts instead of per 10,000 population rates, as this is a less restrictive specification and provides more interpretable results; instead population is a control in the model.[14] We also include 2000 values of

[14] Modeling the foreclosure-crime relationship using counts rather than rates allows coefficients to be interpreted as the increase/decrease in the number of crimes due to changes in the number of foreclosures.

commercial land area (an indicator of the number of businesses) and number of single-family, owner-occupied housing units (an indicator of density and collective efficacy) as controls. Given the distinctive trajectory regimes shown in figures 1 and 2, we estimate separate models for each neighborhood group, as well as in aggregate.[15]

Results

The multilevel growth model results are shown in Table 3.[16], First consider the overall findings across all 80 neighborhoods. As would be expected from Figure 1, the overall trend is negative, with the average number of property crimes decreasing annually by 50 for neighborhoods with no foreclosures in the previous year. As expected, larger neighborhoods have more crimes, but the other controls did not prove predictive. This model includes random effects for the neighborhood time trends – in effect, estimating separate parameters characterizing the property crime time trend in each of the 80 neighborhoods. As discussed above, the random parameters are distributed around the main effects shown in Table 3 and their covariance is estimated as a parameter of the model. For the Overall model, the estimated correlation between the random effects for the overall trend parameters is -0.674, indicating that neighborhoods with larger starting points (i.e., higher property crime levels) have larger annual decreases (i.e., more negative annual changes in the number of property crimes).

Table 3 also shows that the impact of lagged completed foreclosures on property crime across all Chicago neighborhoods is large and highly statistically significant. Each additional foreclosure in the previous year increases the initial number of property crimes by about three-quarters and slows the annual decline in property crimes by 0.14. To put the magnitude of these estimates in perspective, consider an archetypical Chicago neighborhood with 10,000 people during the 1998-2009 study

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[15] Since there are only three or four years (observations) in each period, the model specification used only the linear model of change described above.

[16] The control variables, population, commercial land area, and single-family owner-occupied housing units, were centered prior to entering into the model. This means that the estimated effects for these variables correspond to the effect of deviations from the average neighborhood. For example, the results indicate that neighborhoods with population that is greater than average have higher levels of property crime. It was not possible to estimate the effect of the control variables on the rate of change in the number of crimes as annual data for these variables were not available.

period, evincing the citywide mean number of annual completed foreclosures of 229 and property crime level of 546 and annual decline of 3.35; see Table 1. Now consider what our model would predict if completed foreclosures were to rise annually by one standard deviation (297). The initial level of property crime in such a typical neighborhood would have been boosted by about 683 (125%) and the annual average change would have been an increase of 19 property crimes (compared to a decline previously).

Table 3. Property Crime-Lagged Completed Foreclosures Multilevel Growth Model Results

	Neighborhood Group											
	Overall		**I**		**II**		**III**		**IV**		**V**	
Main effects	.	.	.	.	.	.	.	.	.	.	.	.
Initial level	1724.8	.000	3430.7	.002	1273.3	.000	1571.1	.000	1966.1	.000	2889.7	.000
	(153.6)	.	(1083.5)	.	(208.7)	.	(176.4)	.	(286.8)	.	(310.6)	.
Average annual change	(54.3)	.000	(20.4)	.164	(43.6)	.000	(63.1)	.000	(39.9)	.001	(166.1)	.000
	(7.1)	.	(14.6)	.	(10.7)	.	(13.6)	.	(11.8)	.	(18.6)	.
Foreclosures#	.		.		.		.		.		.	
Effect on level	2.3	.001	(4.4)	.416	1.6	.597	2.8	.011	1.4	.026	15.5	.000
	(0.621)	.	(5.4)	.	(2.9)	.	(1.1)	.	(0.624)	.	(2.6)	.
Effect on rate of change	0.076	.048	0.064	.366	0.196	.100	0.121	0.09	0.039	.504	2.9	.000
	(0.038)	.	(0.070)	.	(0.119)	.	(0.071)	.	(0.058)	.	(0.678)	.
Control variables	.		.		.		.		.		.	
Population	0.031	.000	0.099	.001	0.032	.000	0.030	.000	0.047	.001	0.046	.000
	(0.004)	.	(0.028)	.	(0.006)	.	(0.008)	.	(0.013)	.	(0.007)	.
Commercial land area	95.2	.295	(83.1)	.635	61.5	.372	(294.2)	.433	(319.4)	.246	906.6	.003
	(90.3)	.	(174.0)	.	(68.5)	.	(372.3)	.	(272.6)	.	(290.9)	.
SF-OO housing units	0.037	.241	(0.233)	.112	(0.003)	.934	0.113	.016	0.122	.460	(0.058)	.691
	(0.031)	.	(0.146)	.	(0.034)	.	(0.045)	.	(0.164)	.	(0.145)	.

Source: Authors' analysis of data assembled by Metro Chicago Information Center. ***Notes:*** For the overall model, the statistical significance levels shown to the right of the coefficients indicate the probability that the estimated coefficients' "true value" is different from zero. For the neighborhood models, the statistical significance levels indicate the probability that the coefficients' "true" value is different from the mean effect across all groups. Standard errors are shown in parentheses. SF-OO refers to single-family, owner-occupied housing units. # Completed foreclosures for the year prior to year when property crime is measured

We think these effects are substantial in magnitude. Especially noteworthy is the impact on the *trajectory* of property crime, which has never before been observed. Indeed, when our results are contrasted to those of the earlier literature, the distinctiveness and value of our analytical approach becomes clear. Note that Immergluck and Smith (2006b), Cui (2010), and Ellen, Lacoe and Sharygin (2013) did not find a statistically strong relationship between foreclosures and the *level* of property crime. Our contrary results suggest the clear revelatory value of applying a multilevel growth modeling approach to this investigation so that impacts on crime *trajectories* can be observed.

Table 3 also presents results for the model distinguished by neighborhood group. Note that the neighborhood group model was parameterized such that the statistical tests for the coefficients (reported in the table) are testing whether the effect for the group is different from the mean effect (across groups)[17]. Substantial differences from the overall pattern emerged among neighborhood groups, with the exceptions of groups I and IV. The lack of statistical significance for these groups' coefficient estimates indicates that the effect of lagged completed foreclosures on property crime among these neighborhoods was not different than the overall effect, not that foreclosures did not affect property crime there. In contrast, the statistically significant coefficient for the effect of lagged completed foreclosures on property crime trajectories for neighborhoods in Groups II, III and V indicates that each completed foreclosure in the previous year slows the decline in property crimes among the respective group's neighborhoods by .27, .31 and 2.4 — substantially more than the .14 effect estimated across neighborhoods overall. The group V neighborhoods evinced much stronger effects for lagged completed foreclosures on both the level and trajectory of property crimes than any other group and the overall set of neighborhoods analyzed.

These results indicate moderation of the effect of completed foreclosures on property crime at the neighborhood level. The effects are weakest in moderate income black neighborhoods (Group I) and low income neighborhoods (Group IV), and strongest in high income,

[17] This model also includes random effects to represent neighborhood variation in the property crime trend; inclusion of the neighborhood group effects reduced level of variation in the random effects and the correlation between the random starting level and annual change parameters slightly (correlation: -0.646).

predominantly rental neighborhoods; this group is comprised of neighborhoods with a range of racial compositions (Group V). We can discern no single metric (income, racial composition, or housing stock characteristics) that clearly correlates with these differential impacts; that is, it is not a specific characteristic shared by the neighborhoods in each group which explain the variation in effects across the neighborhood groups. Thus, we believe that a panoply of factors operates synergistically to create this moderation effect, though further research is required to identify these factors more precisely.

Our results counter the conventional wisdom that disadvantaged neighborhoods are more vulnerable to foreclosure-induced crime impacts, which we suggest might be a product of the interplay of several factors. In weaker-market, more-disadvantaged neighborhood contexts (like Groups I and IV), foreclosure upsurges may have less-noticeable incremental impact on crime for at least three reasons. First, there likely are already a comparatively large number vacant (rental and for-sale) dwellings that make for vulnerable targets and facilitating venues for various illegal acts, as well as implying fewer capable guardians (Raleigh and Galster, 2012). Second, signs of decay and disorder may abound before the foreclosure wave, already signaling no collective efficacy for deterring potential offenders. Thirds, acute economic necessities, stressful life circumstances and customs regarding illegal acts may have already established a crime-ridden environment in such neighborhoods. By contrast, the stronger impact we observe in areas comprised predominantly of renter-occupants in large, multi-unit buildings is consistent with the hypothesis that such environs, even if occupied by higher-income residents, have fragile collective efficacy. They might be especially vulnerable to foreclosures in their single-family stock that push them beyond the threshold into social disorder. But besides these behavioral reasons, weaker apparent property crime impacts in disadvantaged and black neighborhoods may also be due to lower reporting rates there (Goudriaan, Wittebrood and Nieubeerta, 2006), though we note that the evidence here appears to be mixed (cf. Baumer, 2002). A final cautionary note: recall that our neighborhoods are expansive in scale; results that run counter to the conventional wisdom should be replicated with our approach at smaller levels of geography if feasible.

Conclusions, Caveats and Implications

We have attempted to contribute to the burgeoning scholarship related to home foreclosures and neighborhood crime by employing for the first time in this field Granger causality tests and multilevel growth modeling with annual data from Chicago. Use of the Granger causality tests enabled the detection and characterization of lead-lag relationships among time series with multiple geographic units and reduced the potential for bias due endogeneity in the specification of the causal model. The multilevel growth model specification allowed estimation of both main (overall) relationships as well as assessment of how the foreclosure-crime relationship varied among neighborhoods, both in terms of level and trajectory effects.

We find that completed single-family home foreclosures temporally lead property crime and not *vice versa*, reinforcing our interpretation of the model parameters as providing strong evidence of an overall positive effect of completed foreclosures on property crime. In particular, an increase in the number of completed foreclosures both increases the *level* of property crime and slows its *decline* in subsequent years. The latter finding is different from the prior literature's. We therefore conclude that it is important to consider the effects on both levels and trajectories, since the latter implies that even a one-period jump in foreclosures can have effects that persist for much longer. Neighborhood characteristics moderate this relationship, likely due to a combination of factors may magnify the effects of completed foreclosures (such as weakening collective efficacy past its breaking point) and/or perhaps influence property crime reporting rates. Our Granger tests failed to show unambiguous, uni-directional causation in the case of violent crime and when filed foreclosures were analyzed.

Before closing we note several limitations of our study. First is potential bias from omitted time-varying variables. While the random effects included in the model parameterization controls for this issue to some degree, we did not have access to inter-census indicators of other neighborhood conditions besides foreclosures that might predict crime; to the extent that such are correlated with foreclosures the estimated parameters of the latter variable will be biased. Second, we did not have access to Chicago neighborhood crime data in shorter periods than annually. Such shorter-period data would have allowed us to explore temporal patterns in more depth. Third, we analyzed only foreclosures for single-family dwellings. The timing and crime-producing effects of foreclosures in multi-unit, owner-occupied buildings and in purely rental buildings may be quite different. Fourth, our model overlooked potential spatial dependence and heterogeneity of error terms. Unfortunately, there are no available software algorithms for dealing with these spatial issues in a multilevel growth model. However, as the members of each neighborhood group are somewhat contiguous, these results do incorporate spatial dependence indirectly. Fifth, this analysis appertains only to Chicago and, as such is not necessarily generalizable. In particular, foreclosures in dwellings that were speculatively built in new suburban subdivisions (as in California, Nevada and Texas) did not characterize the Chicago situation. Of course, this lack of generality is not unique to our study, as all extant work on this topic has relied on one-city case analysis. Finally, since this study was conducted as part of a contracted evaluation of the New Communities Program, we analyzed neighborhoods specified expansively to correspond to the scale of NCP target areas. We recognize that effects that potentially could be found at smaller geographic scales might be washed out at this larger scale, leading to Type II errors. A more geographically disaggregated analysis might reveal additional insights into the phenomenon under investigation, especially distance-decay effects of crime spillovers.

Despite these limitations, we believe that our innovative application of Granger causality tests and multilevel growth modeling to the field of neighborhood crime analysis has proven a useful prototype exercise. Our findings add nuance and reinforcement to a rapidly growing literature that demonstrates the negative impacts of foreclosures on neighborhood crime rates. This lends further testimony to the voluminous evidence about the toll on local housing markets imposed by the United States' latest dalliance with unregulated financial markets (Kingsley, Price and Smith 2009; Immergluck, 2011).

Acknowledgements

This research was supported from a grant from the MacArthur Foundation to MDRC related to the evaluation of the New Communities Program. The opinions expressed in this paper are the authors and do not necessarily represent those of MDRC, the Foundation, or their respective Boards of Trustees

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Appendix 1. Descriptive Statistics of Chicago Neighborhood Conditions, by Group

Characteristic	Neighborhood Group					
	All	I	II	III	IV	V
Population and households						
Population percentage change, 1990-2000	3.6	-5	5.6	20.4	-9.7	13.7
Population 55+, percentage change 1990-2000	-6.8	11.2	-10.5	-13.3	-12.5	1.2
Percentage black	42.7	90.9	10.7	8.8	84.2	20.4
Percentage Hispanic	21	5.3	21	61.4	4.4	12.2
Percentage foreign-born	18.6	3.6	26.9	37	6.5	13.8
Percentage less than high school education	29.3	25.3	22	45.7	34.6	13.5
Percentage unemployed (civilian labor force)	6.8	8.4	3.8	5.8	10.9	4.7
Percentage poverty	20.9	19.9	10.6	17.4	38.1	16.7
Percentage household poverty	19.6	18.6	10.1	16.7	36	14.4
Percentage households public assistance	8.5	11	3.2	5.9	17.1	3.8
Percentage households with earnings	77.1	76.6	80.7	80.9	67.1	84.8
Mean household income ($)	49,646	45,908	57,022	45,826	34,491	78,646
Percentage households single mothers	11.6	15.2	5	9	21.7	4.8
Percentage moved last five years	57.1	68.7	57.7	56	57	38.8
Housing units						
Percentage housing units rentals	47.6	36.8	39.1	44.6	63.5	56.6
Percentage housing units vacant	8.7	7.5	4.2	7	15.6	10
Percentage housing units multi 2 to 4	31.4	25.8	22.9	51	33.9	22.7
Percentage housing units multi 5 or more	32.9	15.9	30.4	11.9	49.8	65
Percentage housing units built in last 5 Years	2.6	0.9	1.7	2	3	8.4
Housing market						
Single-family home purchase loans (N)	2,313	476	1,830	1,127	1,713	10,471
Change in number of loans, 1995-2000	74.6	27.9	43.7	9.2	138.2	207
Single-family home loan mean amount	140	97	155	128	119	232
Change in mean loan amount, 1995-2000	36	33.5	36.3	34.5	36.8	40.4

Source: Authors' analysis of data assembled by Metro Chicago Information Center. ***Notes:*** Shown above is the mean (average) across neighborhoods for the indicated characteristics. Unless otherwise indicated, the reference period for measurement is 2000.

Appendix 2. Average Crime and Foreclosure Rates by Neighborhood Group, 1998-2009

	Crime Rates		Foreclosure Rates	
Year	**Property**	**Violent**	**Filed**	**Completed**
All Neighborhoods				
1998	708.8	228.2	219.1	135
1999	647.5	200.9	264.4	195.4
2000	617.6	191.3	309.9	226.2
2001	563.1	181.5	410.8	316.8
2002	549	178.2	560.6	399.4
2003	547.4	164.7	474.5	382.5
2004	513.9	151.9	367.1	339.3
2005	494.8	156.1	229	183
2006	496.9	154.1	246	86.2
2007	477.6	150.4	429.3	142.7
2008	492.3	145.1	475.8	187.7
2009	446.7	124.6	386.1	155.6
Neighborhood Group I (13 Neighborhoods)				
1998	671.3	263.8	214.9	132.4
1999	622.9	234.9	255.6	181.4
2000	623.2	238.8	265.2	222.1
2001	593.7	234.2	362.3	279.1
2002	582.5	245.2	533.8	376.7
2003	602	232	500.7	424.6
2004	583.2	224.1	379.5	386.5
2005	553.1	228.4	332.8	221.9
2006	564.3	228.5	395.4	148.6
2007	573.5	252.6	504.4	191.9
2008	595.2	239.9	544.3	242.6
2009	516.9	201	400.4	159.4
Neighborhood Group II (24 Neighborhoods)				
1998	379.8	73.4	72	49
1999	345.7	66.1	92	50.3
2000	340.9	64.6	88.7	69.1
2001	312.6	59.8	104	62.1
2002	314.5	56.6	129.9	77.9
2003	301.1	54.9	118.9	71.1

2004	286.5	51.9	98.8	60.4
2005	277.7	49.5	70.6	34.2
2006	264.8	50	93.5	18.9
2007	256.6	45.5	153	41.6
2008	283.7	48.2	217.1	70.3
2009	266.3	42.6	236.3	72.9
Neighborhood Group III (15 Neighborhoods)				
1998	493.4	121	150.2	104.4
1999	463.6	117.2	154.8	116.7
2000	468.9	117.9	177.1	126
2001	433.4	117.6	234.9	140.7
2002	436	117.2	324.6	206.6
2003	433.2	107	297.7	210.6
2004	389	93.7	239.3	172.9
2005	365.3	97.7	139.8	85.9
2006	366.7	98.4	191.2	43.9
2007	347.4	89.4	317.1	102.1
2008	343.2	94.4	489.4	176.3
2009	339	83.9	516.8	185.5
Neighborhood Group IV (20 Neighborhoods)				
1998	899.6	483.4	494.2	291.6
1999	826	416.4	611.4	486.7
2000	736.4	376.3	763.4	563.2
2001	678.5	353.3	1,010.70	876.9
2002	651.9	338.8	1,407.70	1,061.00
2003	666.4	309.5	1,143.30	974.4
2004	618.4	281.7	847	881.5
2005	617.2	295.3	476.3	465.9
2006	627.6	285.5	448.9	184.3
2007	580.5	272.3	924.8	312.3
2008	579.5	253.4	883	366.9
2009	520.8	218.5	570.6	278.6
Neighborhood Group V (8 Neighborhoods)				
1998	1,684.00	197.7	108.9	63.3
1999	1,491.60	168.6	133.5	72.7
2000	1,420.00	169	161.1	49.4
2001	1,219.80	151.2	240.4	72.1

2002	1,153.00	147.4	221.1	108.3
2003	1,113.70	130.9	157.8	90.9
2004	1,056.90	118.6	192.1	56.3
2005	989.1	120.2	84.5	41
2006	1,000.70	121.5	56.2	21
2007	971.3	108.9	107.5	17.6
2008	1,012.10	106.2	96.9	24.2
2009	890.8	88.2	106.3	34.3

Notes: Crime rates are calculated per 10,000 population; foreclosure rates for single-family properties are calculated per 10,000 single-family homes. For both rates, the denominators were calculated from 2000 Decennial Census data. Crime data from Chicago Police Department records, assembled by Metro Chicago Information Center.